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# Applying Machine Learning for Real Time Optimization of Powder Bed Manufacturing

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# Applying Machine Learning for Real Time Optimization of Powder Bed Manufacturing

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# WPI

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# Abstract

Despite continuous growth and improvements in Selective Laser Melting (SLM) systems, part quality and reproducibility are still affected by process instability. The aim of this project is to illustrate improvement in quality and consistency of SLM printed parts by introducing machine learning. In order to achieve this, we set out to build an SLM testbed system with integrated sensing capabilities, and utilize machine learning and in-situ process monitoring to introduce delayed, closed-loop control to the SLM process.

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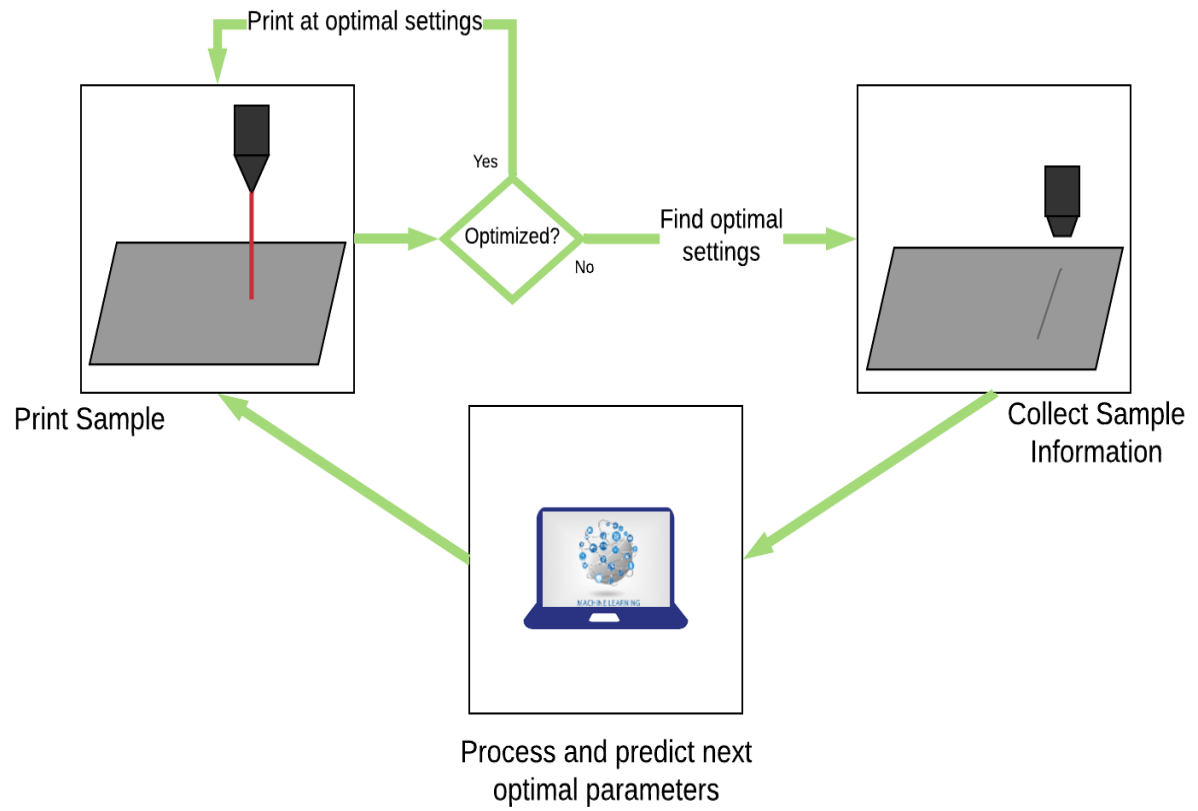
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# 1. Introduction

**Additive Manufacturing (AM)** is defined as the *‘process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative manufacturing methodologies’*[1]. In 2013, the profits of the AM industry was evaluated at \$3 billion. By 2020, it is anticipated that the annual revenue for 3D printing and AM will surpass \$21 billion [2]. Until now, most commercial applications for AM have been using thermoplastics, but metallic parts are desirable because of their improved strength and conductive properties. This is where Powder Bed Fusion and Selective Laser Melting come in.

**Powder Bed Fusion (PBF)** is a subset of AM technologies which selectively fuses regions of material powder, using thermal energy. While this process can only build using materials available in atomized form (powder form), it allows for layer-upon-layer building of complex parts, with rich details and desirable material properties [3]. Due to the abundance of metal powders, PBF systems have quickly become heavily used for 3D printing of metals. **Selective Laser Melting (SLM)** is a form of PBF and according to the American Institute of Physics, “SLM has been proven to produce near net-shape parts up to 99.9% relative density. This enables the process to build near full density functional parts and has viable economic benefits.”[4]

Even though the growth of the AM industry has been rapid over the recent decades and the quality of the additively manufactured parts has improved drastically, there are still major shortcomings and inconsistencies that need to be addressed. Among these shortcomings are poor surface properties, undesired porosity, delamination, and dimensional errors [5]. Part quality issues can be attributed to the AM process parameter settings, typically done by a trial-and-error method for each material which is costly and ineffective. **Our project will focus on SLM technology and proposes the use of a closed-loop control system which utilizes machine learning for real-time parameter prediction, optimization, and control.**



**Figure 1:** General Design of a Machine Learning Enabled SLM System

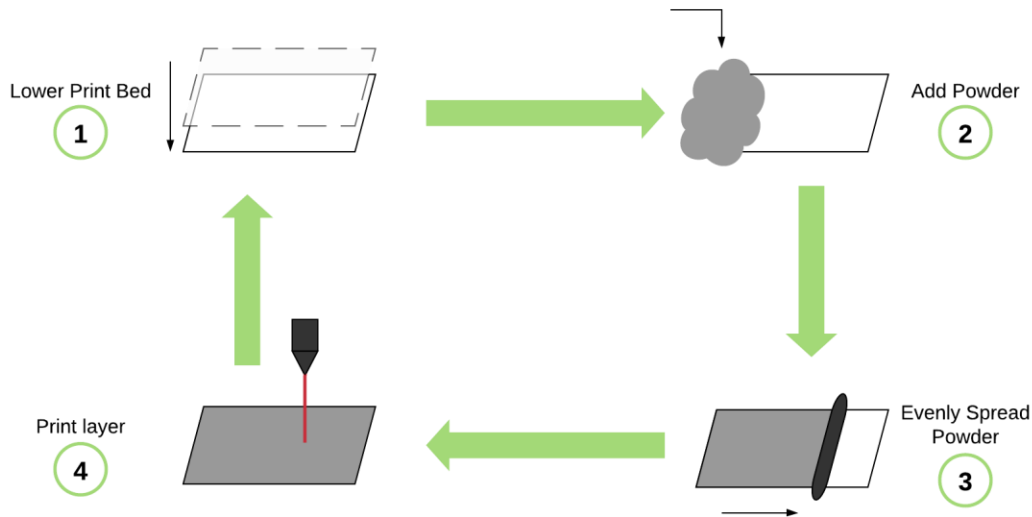


## 2. Background

The purpose of this section is to provide a baseline knowledge and context about some of the key topics addressed in this Major Qualifying Project (MQP). As mentioned earlier, the long term goal for this project was to develop a framework in which machine learning could be used to predict and optimize parameters SLM machines. More specifically, this project focuses on optimizing parameters for surface roughness and developing a framework which can be used for further optimization of various other material characteristics. Previous projects, as researched by the team, had successfully developed recommendations for the selection of various sensors, metal powders etc. and even the most influential parameters inside the process. A few of these papers, research and important terminology will be discussed in this section.

### 2.1 Selective Laser Melting: An In-Depth Explanation

SLM technology uses fiber lasers as an energy source. Depending on the printing media, the laser wattage can be from 7 W (for plastics) and up to a 1 kW. The laser beam is then focused to a spot size of about 100  $\mu\text{m}$  using optical equipment. For printing, a 30-100  $\mu\text{m}$  layer of powder is spread evenly on a flat surface using a spreading mechanism [6]. Subsequently, the laser scans the surface based on programmable patterns in order to melt and fuse the particles together, producing one cross-section of the component. After scanning and solidification of each layer, another thin layer of powder is spread using the recoating mechanism and then scanned by the laser. This process is repeated until the desired component is completed. This process takes place in an enclosed, inert atmosphere in order to minimize oxidation and risk of hydrogen pick up.



**Figure2:** SLM Schematic Outlining the Major Steps of SLM

## 2.2 Influential Parameters in SLM

There are over a 100 different parameters involving SLM technology [7]. The following is a brief description for each parameter that is particularly important for this project's purpose:

### Laser power output

Laser power is the most important parameter in SLM. The laser needs to provide just enough energy on the powder bed for particles to form a metallurgical bond. If there is a large amount of excess energy, the powders will fully melt and form a low porosity specimen but they are susceptible to excessive shrinkage, high residual stress and cracks, as well as other surface defects. Alternatively, if the laser power is too low, there is not enough energy for a homogeneous melt, causing a laminated and porous structure. More detail about the effect of laser output and overall SLM mechanisms is listed in appendix A.

### Scanning speed

The scanning speed is the relative linear speed at which the laser moves with respect to the substrate. The length of time at which the laser spot emits at a each particle dictates the amount of energy transferred to the particles. Similar to the laser power, this affects the properties of the print based on over-melting and under-melting of the powder.

### Laser spot size

Laser spot size is the diameter of the laser beam as it reaches the substrate surface. A well-designed laser head will have a focused beam with a small spot size will have a higher energy density with respect to area, thus transmit the energy more efficiently.

### Powder bed layer thickness

The thickness of each layer is a major determining factor for the average grain size of the printed specimen. Meaning that the largest grain size cannot exceed the thickness of the spread powder layer.

### Powder type

Powder material is one of the most important factors in designing an SLM system. Due to difference in melting point and variance in absorptivity of the laser beam at different wavelengths, a laser with the optimal power and wavelength ratings should be utilized depending on the material.

### Powder shape

A spherical morphology is often preferred for its high packing density, contributing to higher densities in the printer parts and also for their superior flowability which is desired for the spreading mechanism.

### Protective atmosphere

Due to the high temperature, the printed parts are always susceptible to oxidation. In order to prevent this the proper protective gas atmosphere with high purity should be used. Failure to provide the proper atmosphere can lead to decarburization and in turn negatively affect the mechanical properties of the part.

## 2.3 Machine Learning

### Why Machine Learning?

Given the vast number of variables which dictate the metallurgy of SLM printed parts, sometimes cited as high as 100 different input variables, accurately modelling the process using mathematics, physics, and chemistry becomes more and more infeasible. Additionally, it is fairly simple to create a database of parts built using an SLM printer, documenting both input

parameters for the build and the part characteristics, which makes a large volume of high quality example data available to us.

Given the complexity of the problem and the high volume of training data, machine learning presents itself as an excellent choice for creating a framework for consistent part production.

## Machine Learning: An Overview

In their prominent book, “Foundations of Machine Learning”, M. Mohri, A. Rostamizadeh and A. Talwalkar define machine learning as “computational methods using experience to improve performance or to make accurate predictions”. Here, they use the word “experience” to refer to data available to train the model. Machine learning is a branch of artificial intelligence, which deals with mathematical models that can be “trained” to learn from data, identify patterns and optimize problems with a vast number of variables.

Machine learning algorithms are usually divided into four categories[9]:

1. Supervised learning
2. Unsupervised learning
3. Semi-supervised learning
4. Reinforcement learning

### Supervised Learning

Supervised learning algorithms are the most commonly used algorithms by everyday businesses and data scientists. They’re the traditionally thought of algorithms, where human-labeled data is made available to the mathematical model for learning. Supervised learning algorithms model the relationship between the input features and the labeled outputs, thus being able to predict input features for “desired” outputs. Some examples of supervised learning algorithms are Naive Bayes, Decision Trees, Linear Regression, etc.

### Unsupervised Learning

Unsupervised learning algorithms differ from supervised learning algorithms in one main aspect: there is not human expert to label the data. Thus, these models are generally used in applications where humans themselves don’t know what to look for inside data. The model finds patterns inside the data and thus learns relationships and dependencies between different data points through self-taught rules. Some examples of unsupervised learning algorithms are K-means clustering, Association Rules, etc.

## Semi-Supervised Learning

Semi-supervised learning is a hybrid of the above mentioned algorithms. They're used when the labeling of a large volume of data is very expensive or infeasible and thus the data provided to the model is a combination of labeled and unlabeled data. These models utilize both sets of data and usually perform better than unsupervised learning due to the availability of the small volume of labeled data- and are more cost efficient and easier to train than supervised learning, where all the data needs to be labeled (usually by humans). Some examples of semi-supervised algorithms are low-density separation, generative models, and graph-based methods.

## Reinforcement Learning

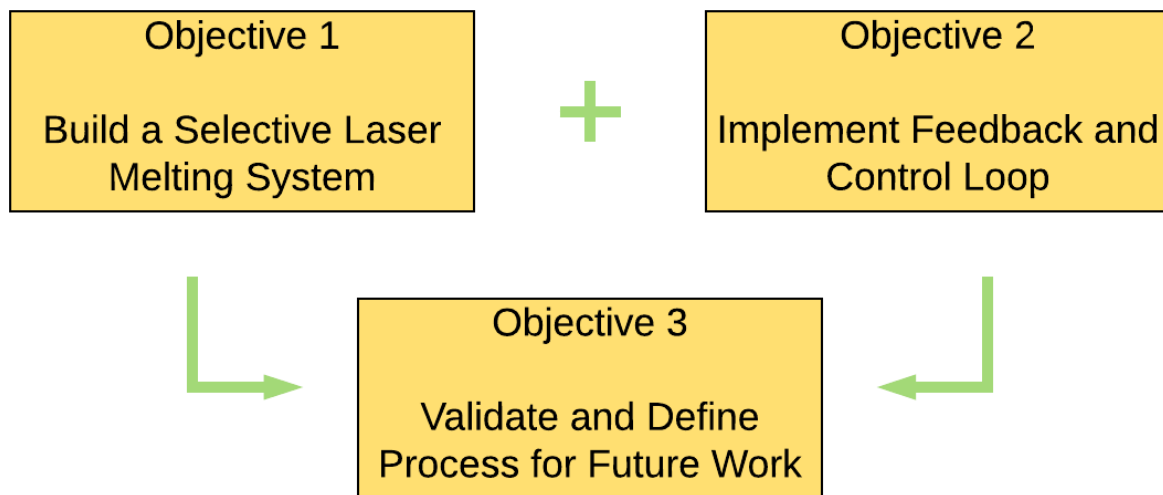
Reinforcement learning algorithms iteratively learn “good” behavior by interacting with their environment. They learn through principles similar to supervised learning, but instead of having a large volume of labeled data, the model has to “interact” with the environment, which in turn produces a positive reward or a negative punishment. This feedback reinforces the behavior of the model, thus giving it the name. Reinforcement learning algorithms often use the terms exploration and exploitation, which refers to taking action that produces the highest possible reward exploitation and taking action that has not been taken before exploration. Using a combination of these two techniques, the model can slowly learn more about the environment, while understanding inputs that lead to positive rewards optimal solutions. Some examples of reinforcement learning algorithms are Q-Learning, Temporal Difference and Deep Adversarial Networks.

### 3. Design and Methodology

The goal of this project was to use machine learning and in-situ process monitoring to introduce delayed, closed loop sensing and control to the SLM printing process. To complete this goal, the project was broken into three major objectives:

1. Build a Selective Laser Melting system
2. Implement a feedback and control loop
3. Validate the results and define future work

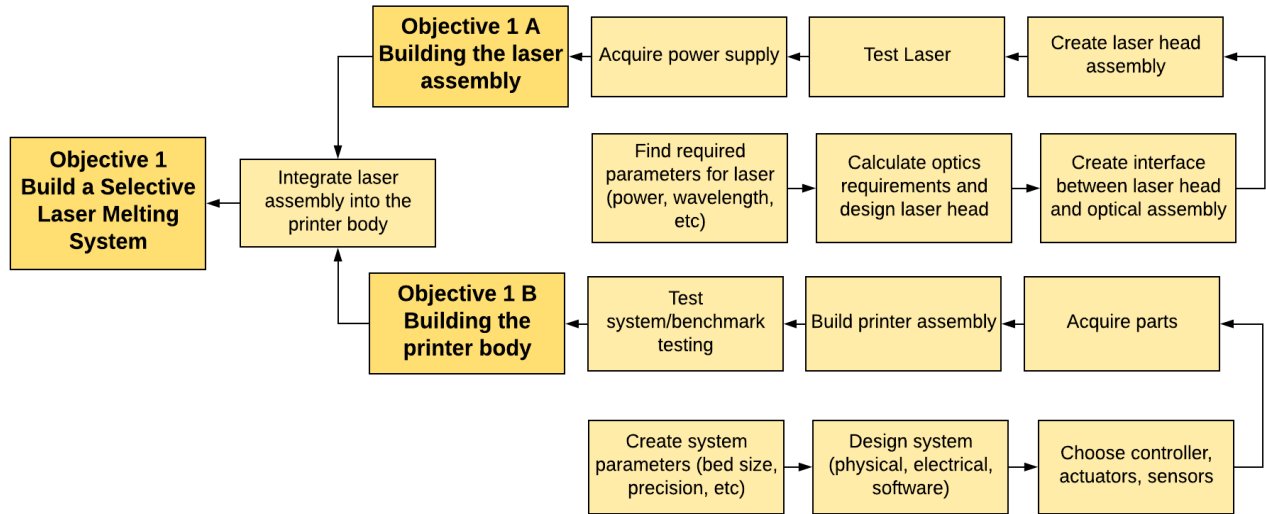
The diagram below shows the three major objectives of the project. The first and second objectives are combined together to create a smart SLM 3D printer, which is then validated in objective three.



**Figure 3:** Major Objectives of the Project

#### 3.1 Objective One: Build a Selective Laser Melting System

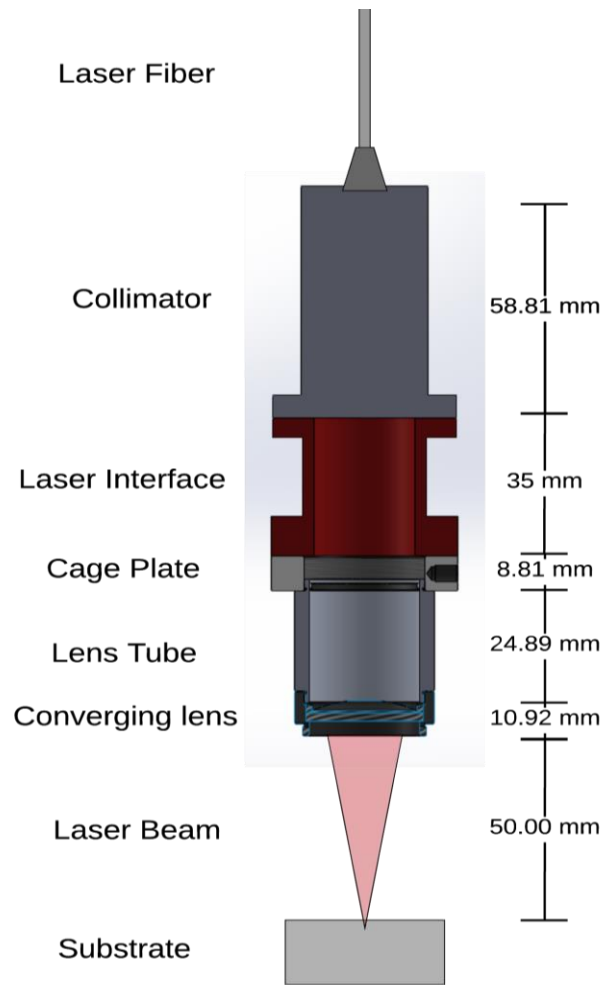
The first objective of the project was to construct a working SLM 3D printer. The final printer system can be broken into two integrated subsystems, a laser assembly and the printer body. Research was conducted to define parameters that would guide the system design for both subsystems. Components for the subsystems were chosen during the second half of the design phase, which were then acquired and used to construct the subsystems. The figure 4 represents this process.



**Figure 4:** Steps of Achieving Objective One

### Objective 1A: Building the Laser Assembly

An IPG photonics dlm-60 laser capable of generating power output of 60-100 Watts at a wavelength of 970 nm was chosen for its high absorptivity by aluminum powders. In order to have a focused laser beam and reach the desired laser spot size, an optical assembly for the laser was designed, built, and attached to the already existing laser head. The laser came equipped with a collimating lens at the head, which is shown in figure 5 at the top labelled collimator. The optical assembly is shown including the cage plate and lens tube parts. To connect the assembly to the laser head, a laser interface part was created and 3D printed, which is shown in red in the middle of the image.



**Figure 5:** Schematic of the Laser Head Assembly

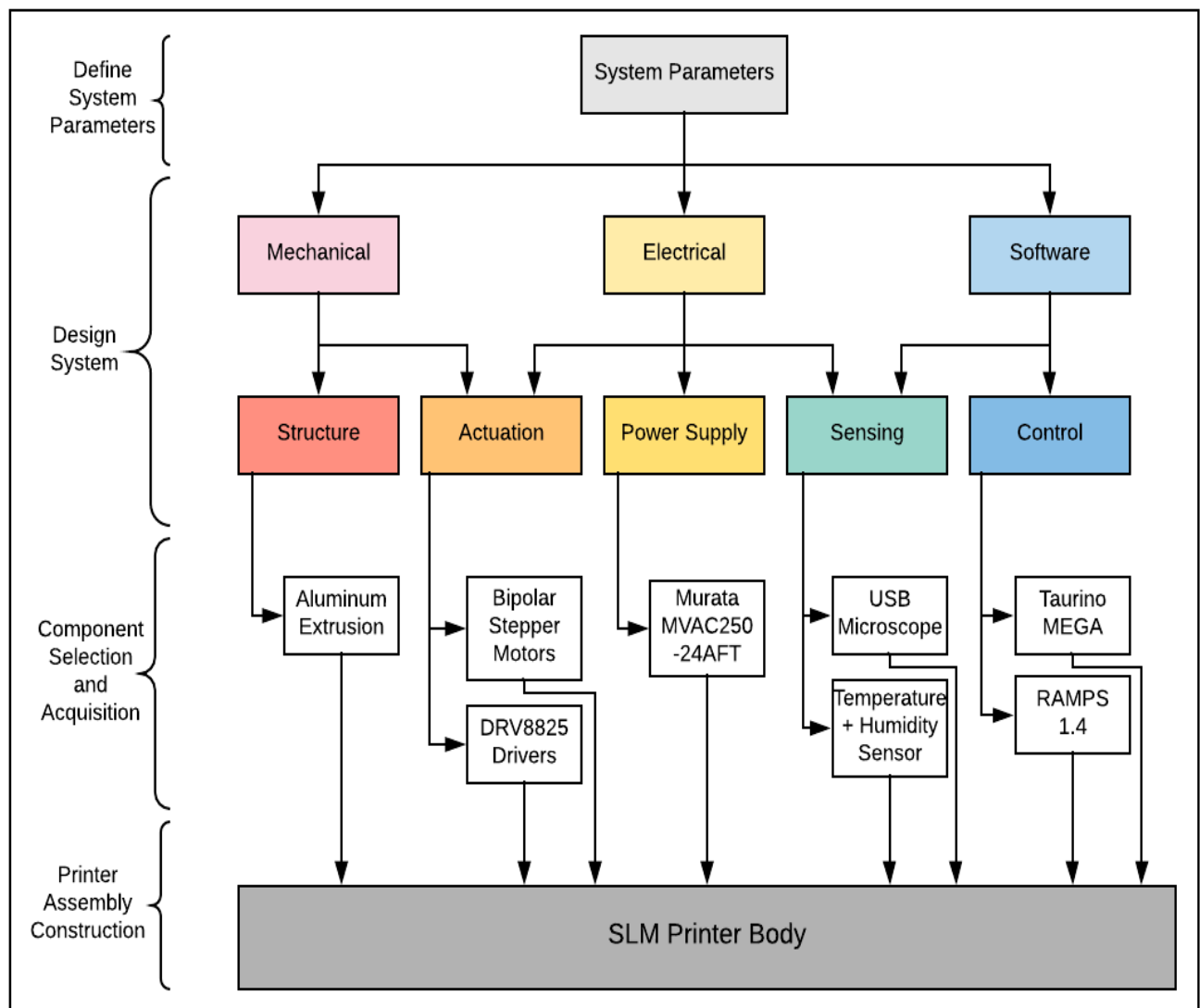
The laser operates at a constant, fixed voltage while current is varied to modulate laser power. As the voltage supplied to the laser increases to the threshold voltage, the current begins to increase until it reaches a stable point when the voltage is slightly higher than the threshold voltage. For this laser, the threshold voltage is 15 volts. Around the threshold voltage, small changes in voltage result in large changes in the amount of current supplied to the laser. This behavior can be used to control the supplied current by controlling the input voltage using a voltage controller.

### Objective 1B: Build the Printer Body

One half of the SLM system is the printer body that contains the systems to power, control, and move the laser to produce SLM parts. The subgoals necessary to complete the printer body are



detailed in the figure below, which summarizes the process to complete Objective 1.B. First, the system parameters are defined based on the project goal and research into contemporary printer designs. Next, the printer is designed. This design covers disciplines of mechanical, electrical, and software engineering, which cover subsystems of the printer. In figure 6, colors are used to denote the discipline, with interdisciplinary subgroups using secondary colors to show the synthesis of two fields. Once the design was finished, components were selected. The major component(s) of each subsystem are shown figure 6. Finally, the components were used to construct the printer body.



**Figure 6:** Subsystems of the Printer Body

## Define System Parameters

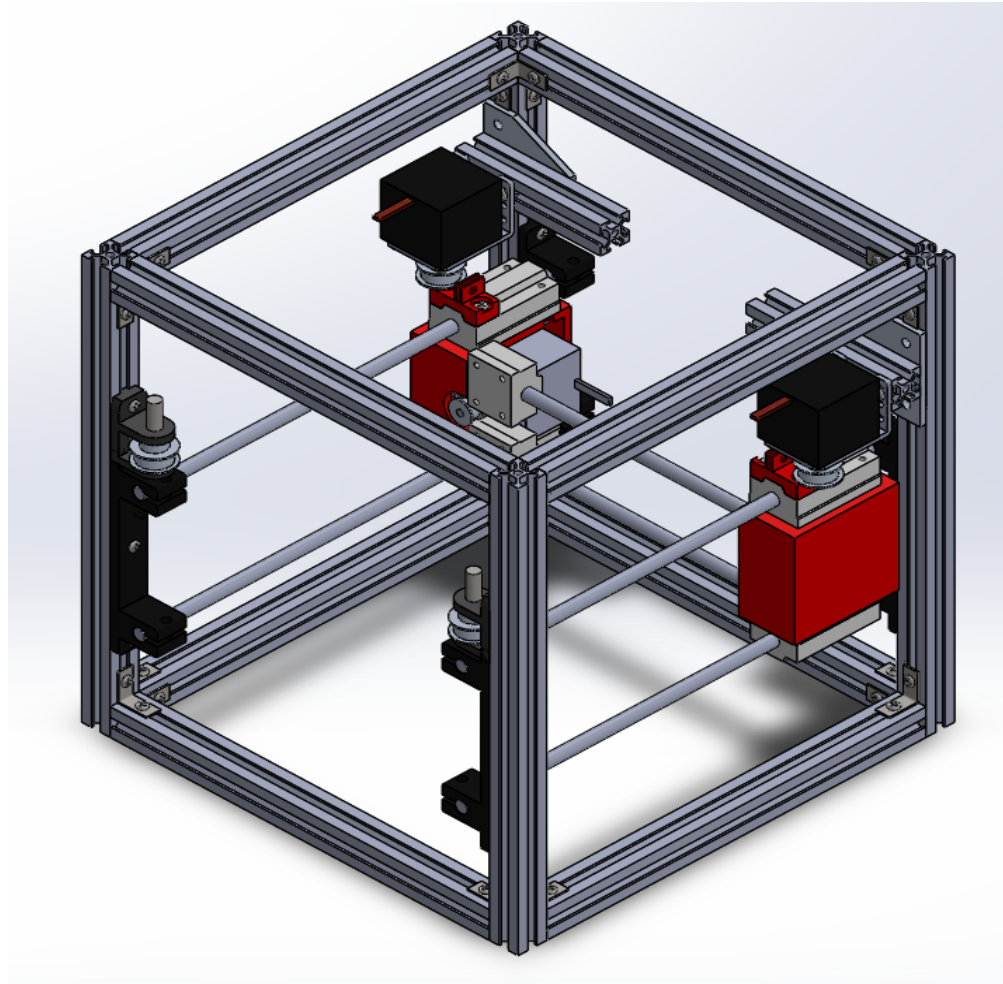
Defining parameters for the printer was the first step towards constructing the system. After conducting research into contemporary designs, realistic parameters could be chosen that were within the time and budget constraints of the project. Important parameters for the printer were the precision and speed of the actuators, the size of the print area, and being able to maintain an oxygen-free environment during printing. It was also important to consider the size of the laser assembly and in-situ sensors during this process, as the printer needed to be large enough to contain the laser with enough room to change the offset from the print bed and also fit sensors that could measure relevant data during the printing process.

## Design System

The design of the printer can be broken into three disciplines, including the mechanical design, the electrical design, and the software design. The design was aided by research into contemporary printers, as well as the parameters that were previously defined. The physical, electrical, and software aspects of the design were pursued simultaneously, which created an opportunity to consider the impact of components on each other and the system as a whole. This was coupled with a focus to reduce the future challenges of adding or subtracting components and keeping maintenance simple. Designing to allow for future modifications or added capabilities was important because this project is a testbed that will lay the groundwork for future research into this area, and it is unknown what modifications may need to be made to the system to allow it to function properly in the future.

Multiple iterations of design were performed before the final design was chosen. It was decided to print single layered, 2-D lines, isolating laser power and scanning speed parameters in order to develop a baseline understanding of the effect of laser power density on part quality. Printing in this manner would omit more complex parameters such as heat dissipation between subsequent layers and powder application methods from consideration as important factors affecting the part quality.

A single layer printer was pursued in the final design iteration. The XY-axis gantry would be used to move the laser over the print area, and a substrate would be placed at the bottom of the printer with a single layer of powder spread over it. The gantry would then move the laser over the print area to produce single layer parts. Multiple designs for the gantry were considered before the final design was selected. The final design can be seen in figure 7.



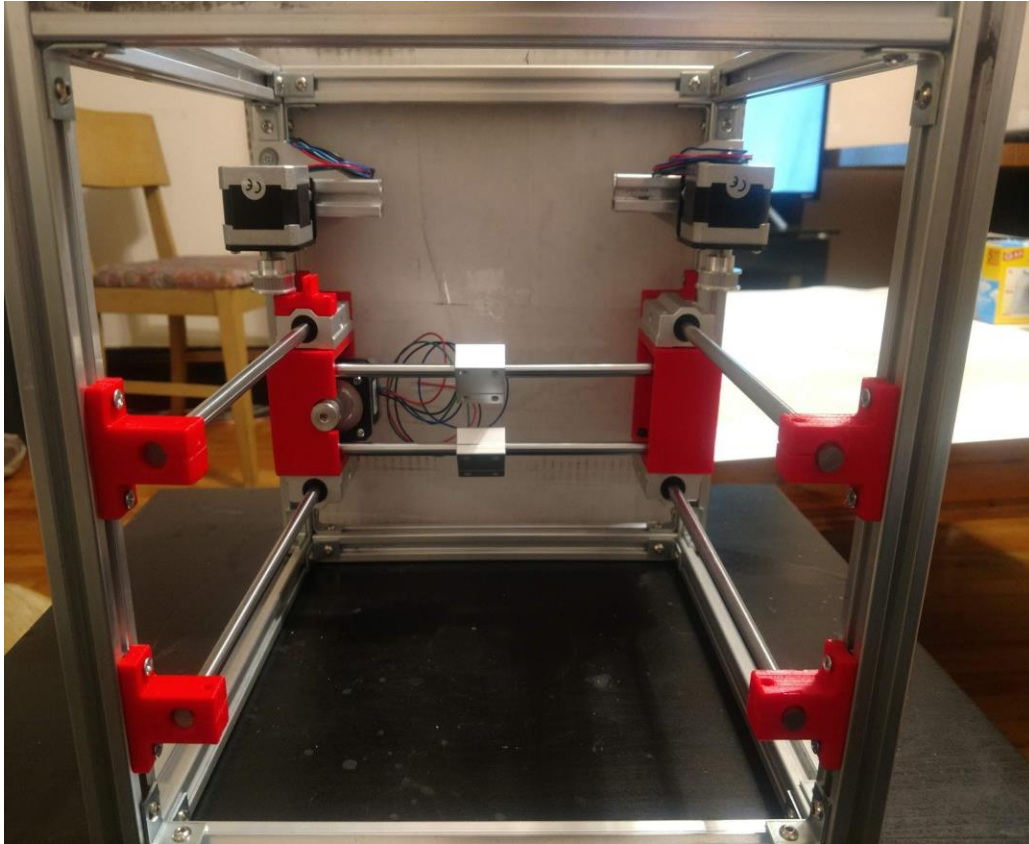
**Figure 7:** Rendering of Printer Body's Final Design

### Component Selection and Acquisition

Throughout the design phase, components were chosen that could fit the needs of the project in terms of capabilities, lead time, and price. Off the shelf parts were favored wherever possible because they provide standard interfaces and reusability. The I<sup>2</sup>C protocol was chosen for communicating between the sensors and the control board because it can communicate with over 100 devices using only four wires, providing plenty of potential for growth in sensing capability. To keep the design organized, the printer was designed as a series of integrated subsystems, including the control, actuation, structure, power supply, and sensing systems.

## Printer Assembly Construction

The printer was constructed in stages, with the frame being constructed first, and then the actuation system being attached to the frame. Figure 8 shows the printer with X and Y gantry as well as actuators. The X axis is perpendicular to the page, the Y axis is across the page.



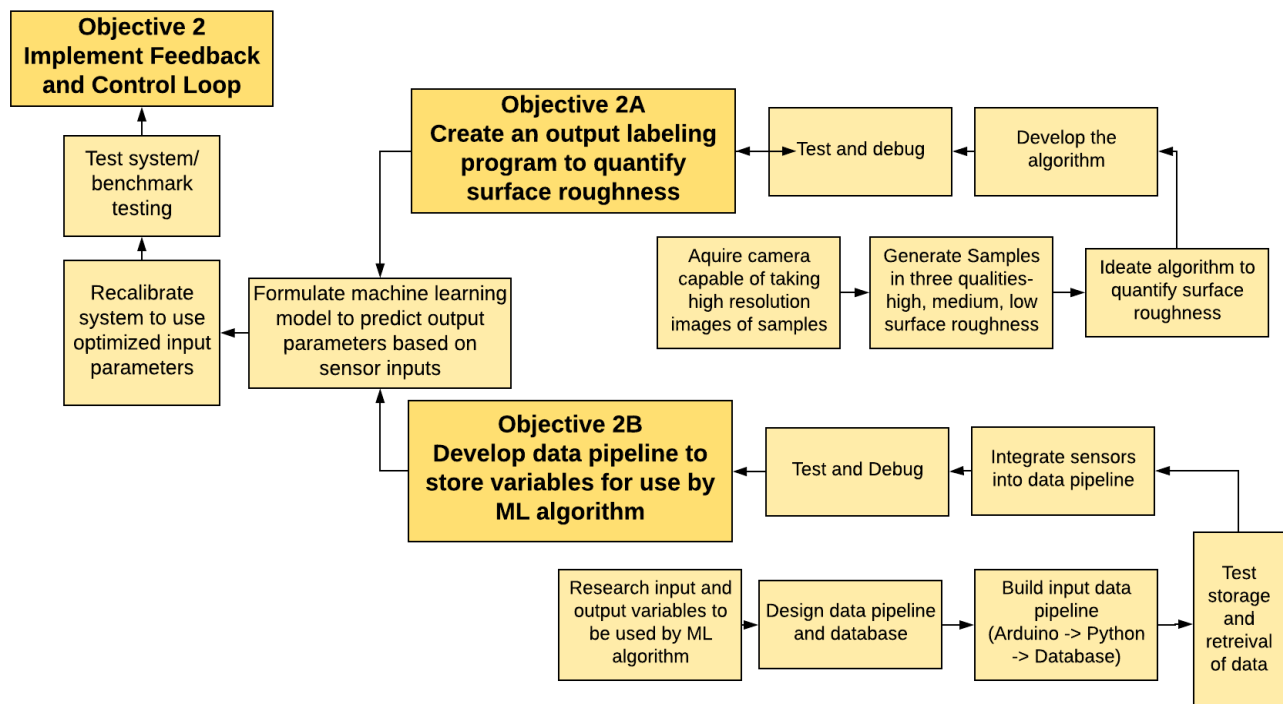
**Figure 8:** Printer with X and Y Gantry with Actuators

## 3.2 Objective 2: Implement Feedback and Control Loop

The second objective was the design and implementation of the feedback and control loop system on the SLM printer constructed in the first objective. Before implementing this system, we deliberated the most feasible material property to optimize, and decided upon surface roughness due to its correlation with part quality (Appendix A). In order to achieve the machine learning goal, two sub-objectives were created:

1. Create an output labeling program to quantify surface roughness
2. Develop data pipeline to store variables for use by machine learning algorithm

These sub-objectives address two crucial parts of the feedback and control loop: the output labeling program would accurately quantify surface roughness, thus providing the machine learning algorithm with feedback. The data pipeline would be used to collect and transfer information between the Arduino, which controls the printer, and the computer, which processes data to provide the Arduino with instructions. The computer-Arduino communication represents the control aspect of the loop. The flowchart shown in figure 9 showcases how these sub-objectives will be achieved.



**Figure 9:** Steps of Achieving Objective Two

## Objective 2A - Create an output labeling program to quantify surface roughness

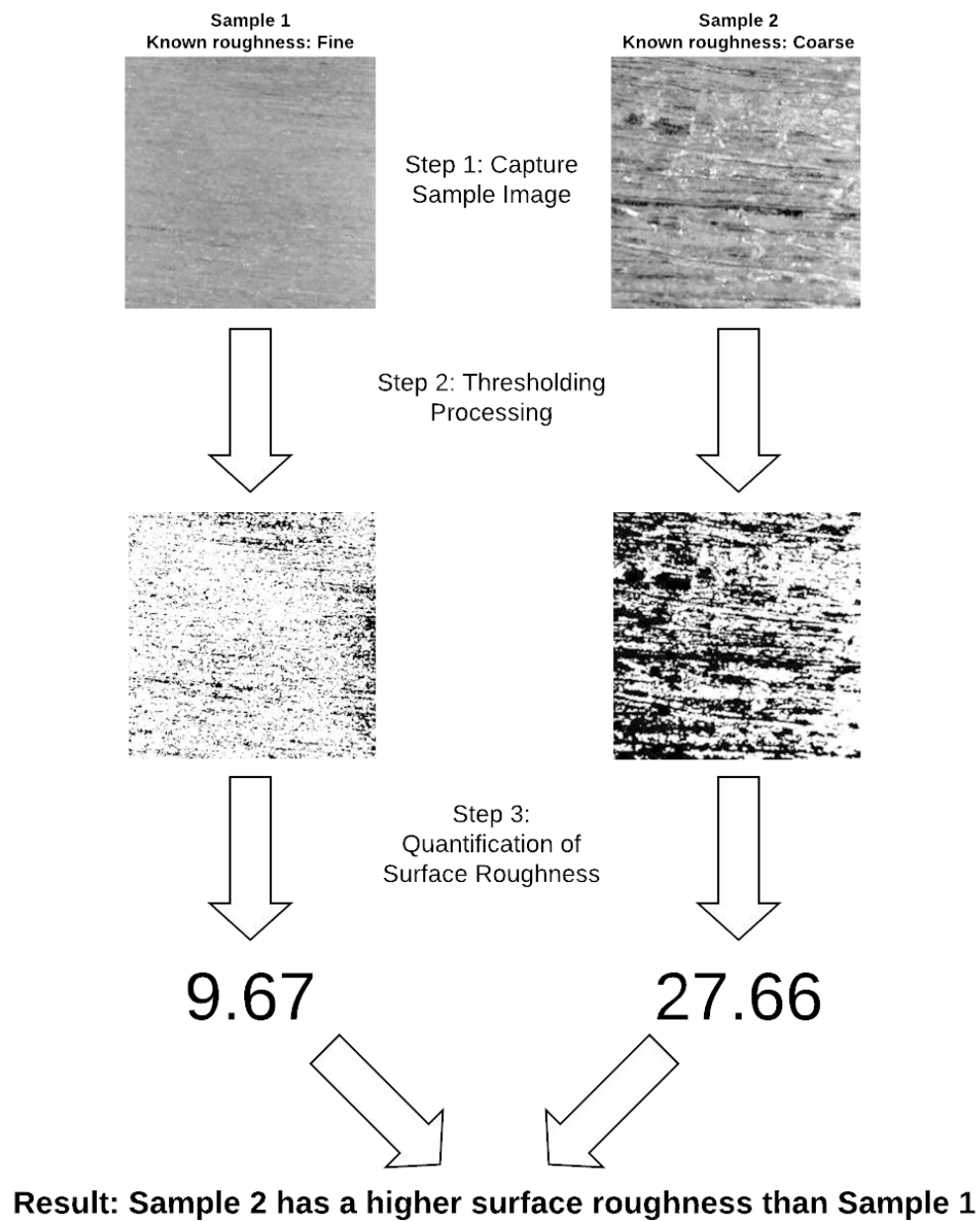
A method for quantifying the property had to be developed in order to optimize the surface roughness of parts using machine learning. This would allow for the sample data collected to be labeled based on its surface roughness and thus be used in a supervised/reinforcement model. The value of surface roughness, based on this program, could be used as a loss function, which the machine learning algorithm would try and minimize to create the smoothest surfaces possible.

The first step in building this algorithm was to create a test set of sample images with known different surface roughness values. Images shown in Figure 10 are some examples from this set:



**Figure 10:** Sample Images from the Algorithm Testing Data Set. From left to Right- Fine Sample, Medium Sample and Rough Sample

An output labeling program was needed to quantify the surface roughness in the above images. For this, a custom algorithm was built using pixel thresholding, based on the principle that a surface with less surface defects and irregularities would reflect light in a more homogenous manner. Since the homogeneity of pixels in an image could be captured, this allowed for the quantification of surface roughness across the images.



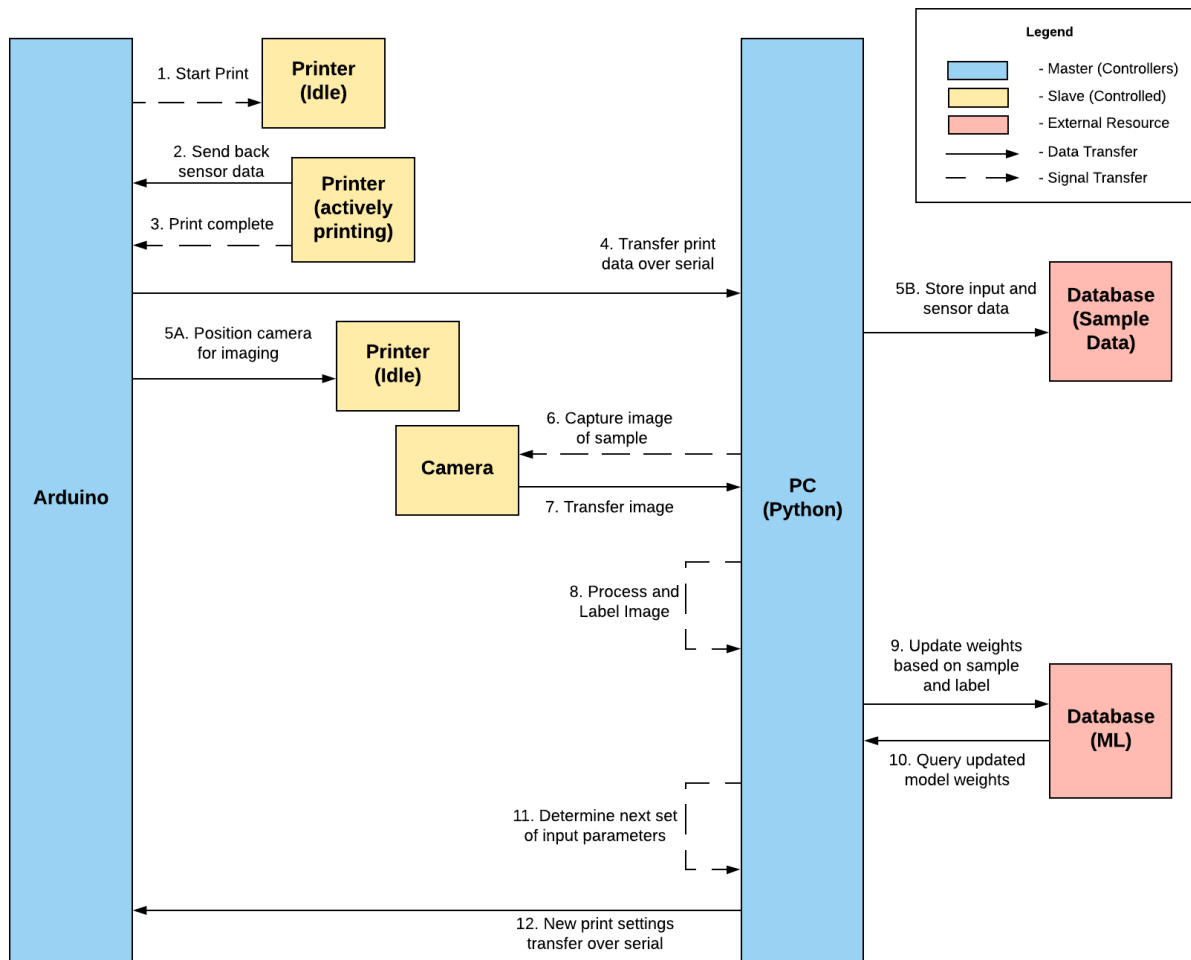
**Figure 11:** Schematic Showing the Output Labeling Algorithm Quantifying and Comparing Two Images

The custom output labeling algorithm that was developed and performed with high accuracy. It was tested across 75 pairings between samples with different surface roughness and the algorithm was able to correctly classify the samples with 96% accuracy (72 out of 75 correctly).



## Objective 2B - Develop data pipeline to store variables

In order for the machine learning algorithm to process the data collected by the sensors, label outputs using the labeling program, and pass input settings to the printer, a robust and low latency data pipeline was required. This pipeline was developed using python and communicated with the printer through serial communication. The diagram in figure 12 outlines the flow of events and data in between the different components of this project:



**Figure 12:** Schematic Showing Data Pipelines Associated with the System

As the above diagram shows, all of the data transfer between the Arduino and the Python program occurs over serial. Serial communication was chosen due to its wide support, existing implementation packages, and simplicity. The data pipeline is instantiated through the Arduino, which signals the printer to start a print. This shifts the printer from its idle state to actively



printing. All throughout the print, the sensors mounted on the printer collect information which is retrieved and locally stored by the Arduino. Once the print is complete, the Arduino receives a completion signal. The completion signal triggers a data transfer between the Arduino and the computer over serial, where the computer receives the sensor data from throughout the print. Once the transfer is completed, two steps occur at once: the Arduino signals the printer to position the camera for imaging and the python program stores the sensor information in a local database. After this, the computer uses the onboard camera to capture an image of the sample and store it locally. After the image is captured, the output labeling program is run to label the captured image.

Following the labeling of the captured image, the Python program updates its machine learning model weights, which in turn are stored on an external database. At this point, the local model will decide the next optimized print settings based on the results from the last build and instantiate the next print.

## 4. Future Work

At this point, none of the major objectives has been fully completed, but good progress has been made towards the completion of objectives one and two:

- A robust output labeling with an accuracy of 96% has been created for in-situ surface characterization of printed parts
- The laser assembly, capable of providing optimal laser beams for aluminum based SLM has been created
- A printer body capable of XY actuation to manipulate the laser assembly has been constructed
- Data pipeline for storage of process variables has been created

To successfully achieve the project goal, future work needs to be done in integrating the laser assembly into the printer and making the printer airtight so that parts can be printed without oxidation. Following this, the machine learning model will be ideated in conjunction with the data collection. After creating a thorough database of samples, we will then train the model and validate the optimization using traditional surface metrology techniques. After the completion of the aforementioned tasks, it is expected that the system will use the machine learning algorithm to control the SLM process and continuously improve surface characteristics of prints.

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## 6. Appendices

### 6.1 Appendix A: SLM Theory

#### **Sensor Selection:**

In order to acquire real-time feedback on part quality, a sensing system was put in place. Initially, a number of devices were considered including IR thermal cameras, tomography devices and meltpool dimension and temperature monitoring devices. Due to various cost and time constraints, the in-situ optical apparatus for measurement of surface roughness was developed in-house. This decision was also due to the realization of relation of surface properties to the overall quality of the printed part, and defects as. These relations are listed the following section.

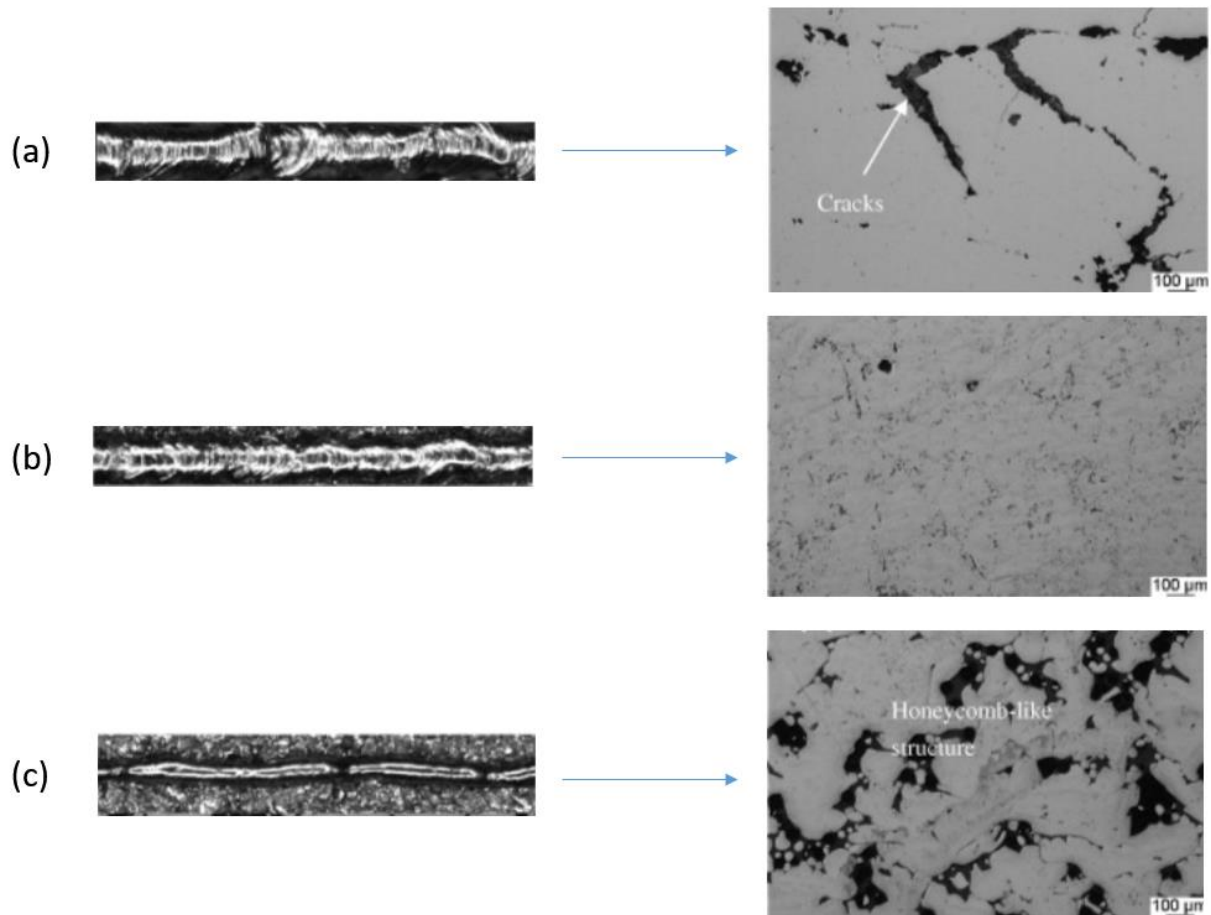
#### **Mechanisms of Selective Laser Melting:**

Depending on both the process parameters such as spot size, laser power, scan speed, layer thickness and powder properties such as particle size, morphology, thermal conductivity, emissivity, liquid surface tension various melting and solidification mechanisms can occur. Song et al., splits these mechanisms into three main categories:

(I) *Melting with Defects*. At high power density (high laser power and low scanning speed), the powder is completely melted in a single track which is susceptible to excessive shrinkage, high residual stress and multitude of large cracks. These prints produce dense, low porosity parts but, they often include a multitude of cracks, split surfaces and other surface defects.

(II) *Continuous Melting*: At the optimal power density, the powder is continuously and completely melted along a single track with no visible defects. These prints benefit from high density and minimum sub-surface defects such as porosity. The particles are metallurgically bonded together along the entirety of the track.

(III) *Partial Melting*: At low power density (low laser power and high scanning speed) there is insufficient energy output that cannot induce a homogenous and full melt of the powder which inevitably causes a laminated and porous structure. These parts include both unmelted or partially melted particles as well as balling which is caused by the melting instability of the process. This instability in melting, caused by lack of sufficient energy, results in decreased dimensions of the tracks and transverse shrinkage distortion in the subsequent tracks.

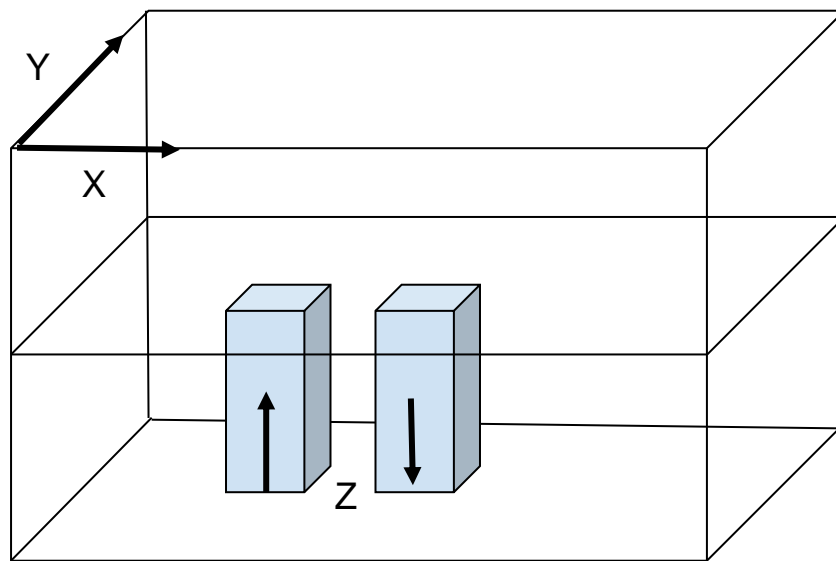


**Figure 13:** Micrographs of 2-D single tracks (left) corresponding to cross sectional view of 3-D parts (right) produced by different processing parameters (a) 120 W, 0.2 m/s (high power density), representing melting with defects mechanism (b) 110 W, 0.4 m/s (optimal power density), representing continuous melting, and (c) 110W, 1.2 m/s (low power density) resembling the partial melting mechanism. [6]

Song's study is evidence that categorization of the surface of a single line of and SLM printed part (2D) based on the overall shape and surface roughness, can confirm properties and predict defects of a fully printed (3D) part.

## 6.2 Appendix B: Robotics

The first design iteration concept was a printer with an XY-axis gantry to move the laser and two Z-axis powder platforms. The first platform would be used to hold powder, and the second would house a build plate. During the print process, the first platform would raise to push fresh powder into the printer while the second platform lowers an equal amount. Then a screed would push the powder from the first platform to the other platform, where it can be melted by the laser. As each layer of the print is completed, the build platform lowers, allowing 3D parts to be built. This design can be seen in the image below.



**Figure 14:** Drawing of the Earliest Prototype

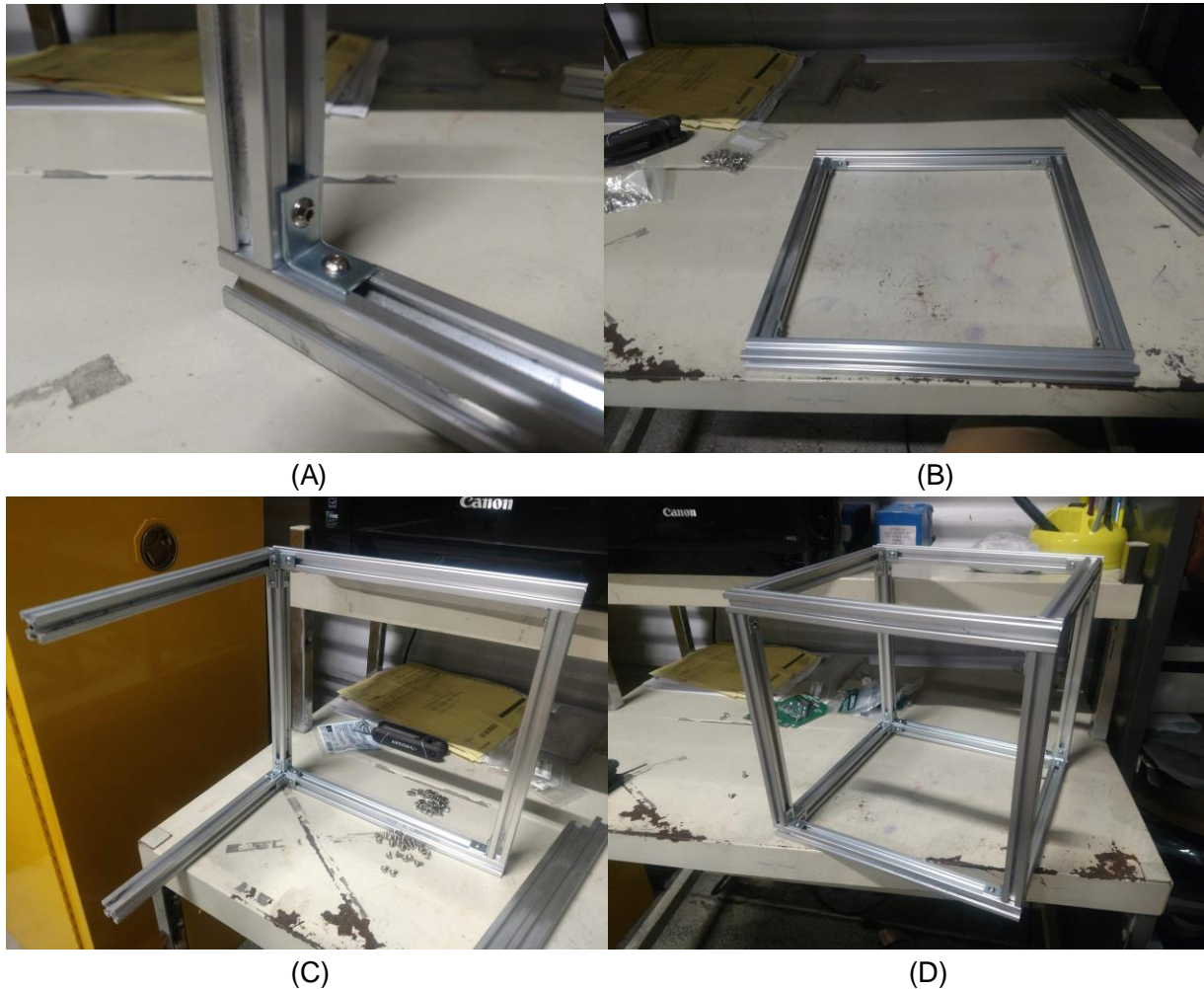
As an example, aluminum extrusion was chosen for the frame of the printer because it can be repurposed for different configurations through non-destructive attachment to other pieces of extrusion or other components. This principle also extended to the electrical and software subsystems.

A bill of materials was created to keep track of the parts needed for the various subsystems of the printer assembly. Components that could offer the necessary functionality at low cost were prioritized, especially if they included opportunities to scale the capabilities of the printer in the future. Once the parts were added to the bill of materials, the parts were ordered by the project's sponsor. When parts were delivered to the sponsor site, they were checked to ensure they

matched the design specification. For example, the power supplies were tested to confirm that they were producing the correct voltage and current.

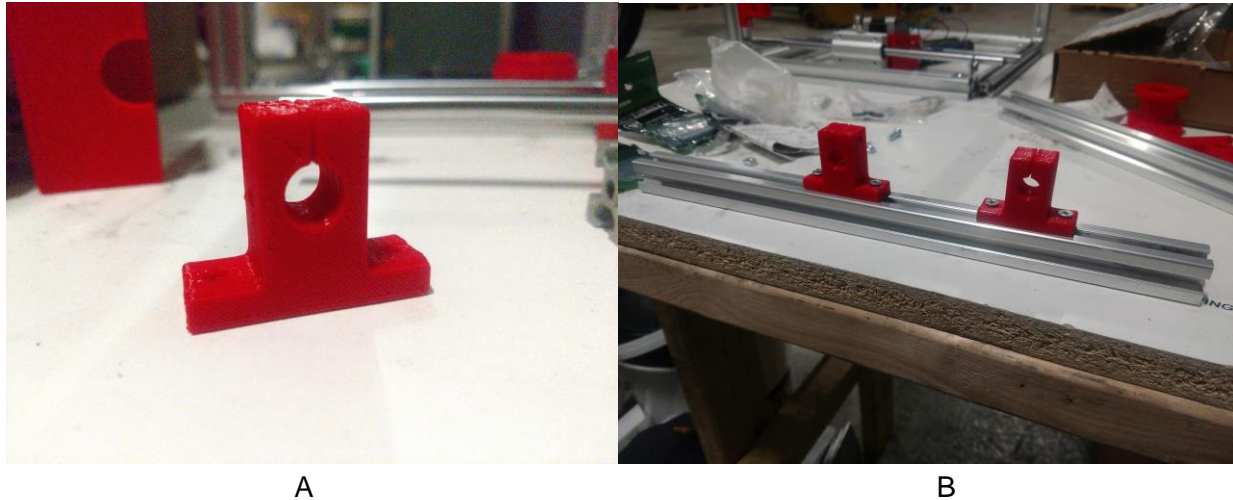
The printer must maintain an oxygen-free environment to prevent the highly flammable powder used for printing from catching on fire or exploding, damaging the printer and causing a large safety risk.

Below are a series of images detailing the construction of the printer in stages.

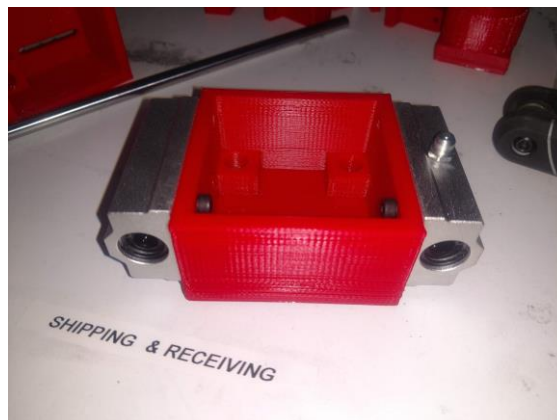


**Figure 15:** (A) shows a detail view of the brackets used to join the individual aluminum pieces into the frame. The pieces were cut into two sizes, 10 inches and 12 inches, which allowed for the construction of a one foot cubic printer frame. In (B) one square of the frame is visible. Two square frames were constructed, and as is shown in (C), joined with cross pieces to form the cubic frame in (D).

Once the frame was assembled, the actuation system could be mounted inside it. The actuation system consists of an X-Y style gantry that is housed along the sides of the printer to leave the maximum possible space open in the interior as a print bed. Below are a series of images depicting the construction of the gantry system inside the printer frame.



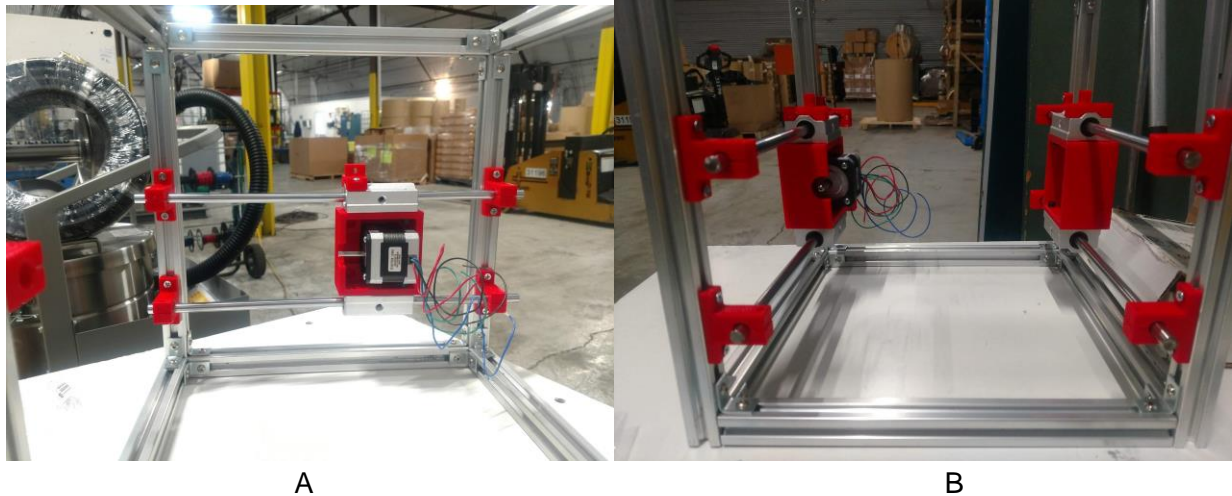
**Figure 16:** The X-axis moves along 8mm diameter smooth rods attached to the frame by 3D printed rod holders as illustrated in Image A. For stability two rods are used, this is seen in Image B.



**Figure 17:** Assembly of Pillow Block Linear Bearings and a Carriage.

Two linear pillow block bearings are used to guide the X-axis carriage along the smooth rods. In between them is the 3D printed X-axis carriage, which is used to house the actuator for the Y-axis and has attachment points for the Y-axis 8mm smooth rods. The rod holders, smooth rods, and carriage assembly can be seen in Image A below. In Image B, both assemblies can be seen. Note that only one carriage has a motor mount. On top of the carriage assemblies are 3D printed tabs to connect the carriages to the actuators.

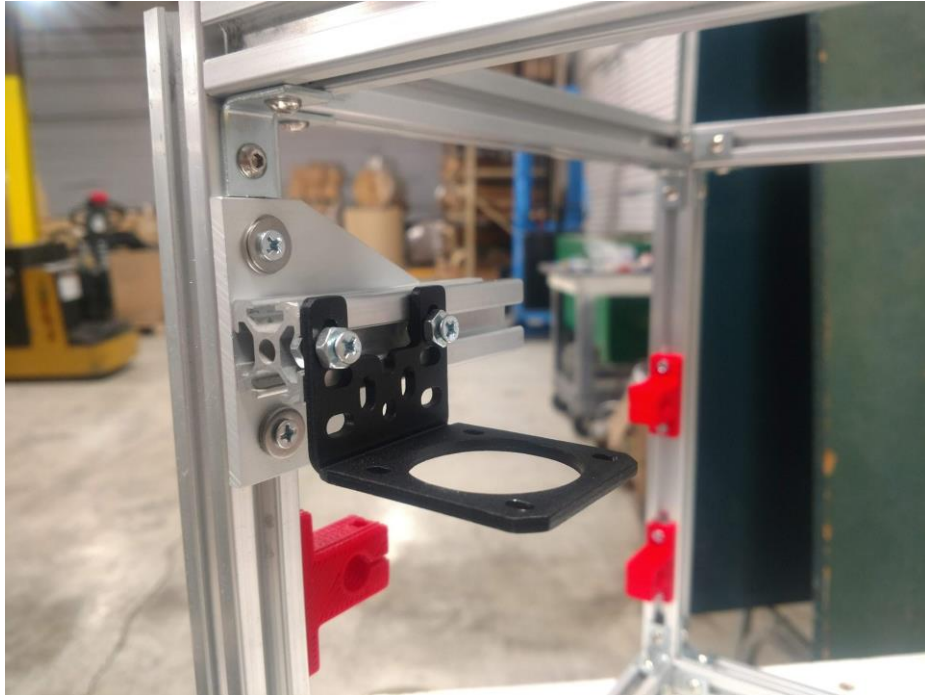




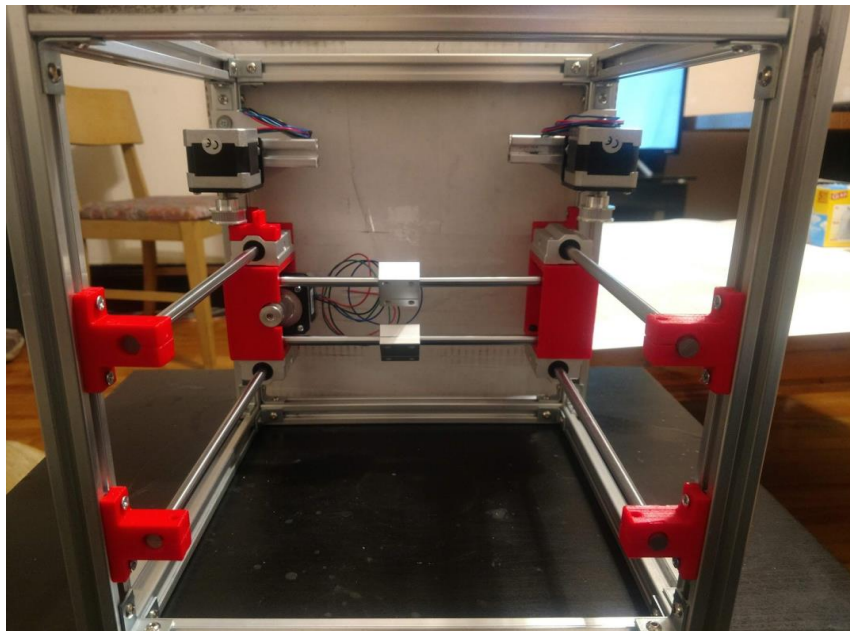
**Figure 18:** The X-axis is actuated by a pair of bipolar stepper motors. Bipolar stepper motors were chosen for their high speed and accuracy for a low price. The stepper motors drive stiff belts that are attached to the X-axis carriages by 3D printed tabs, as seen in Image B. A bipolar stepper motor can be seen in the image below, with the gear used to interface with the belt secured to the end of the axle.



**Figure 17:** Bi-polar Stepper Motor



**Figure 18:** Assembly used to attach the motor to the printer frame. The motor is seated in the black mounting bracket, which can be adjusted along the small horizontal piece of aluminum extrusion. The horizontal piece is attached to the frame by an aluminum T-junction, which can be adjusted vertically. In the image below, the full X-axis actuation system can be seen. The Y-axis with associated pillow block bearings is in between the two X-axis carriages.



**Figure 18:** Full X-axis Actuation System